A Joint Estimation Method to Combine Dichotomous Choice CVM Models with Count Data TCM Models Corrected for Truncation and Endogenous Stratification

Abstract

This research updates the joint estimation of revealed and stated preference data of Cameron (1992) to allow for joint estimation of the Travel Cost Method (TCM) portion using count data models. Further, these count data models reflect correction for truncation and endogenous stratification associated with commonly used on-site recreation sampling. Our updated modeling framework also allows for testing of consistency of behavior between revealed and stated preference data rather than imposing it. Our empirical example is river recreation visitors to the Caribbean National Forest in Puerto Rico. While we find little gain in estimation efficiency in our data, this may be due to our contingent valuation question eliciting willingness to pay for existing site conditions, a benefit measure conceptually very similar to what is estimated with TCM. However, our updated joint estimation may make a significant improvement in estimation efficiency when the contingent valuation scenarios involve major changes in site quality not reflected in the TCM data.

JEL Classifications: Q0 Agricultural and Natural Resource Economics

Key Words: Nonmarket valuation, Travel Cost Models, Contingent Valuation Models, Recreation

Introduction

Determining the consistency of Stated Preference (SP) and Revealed Preference models (RP) has been an important part in the recreation economics literature for more than two decades. SP uses hypothetical scenarios to create or extend existing market conditions for a public good and assess marginal consumer behavior to change in fees or quality. RP considers observed behavior from consumers to uncover a demand schedule usually to arrive at the benefit consumer receive with the current price and quantity. Neither of the available methods under both types of models is free of criticism. SP models, typically developed in the form of Contingent Valuation methods (CVM), are of concern because of the hypothetical nature of the "transactions" used. Although several validation studies have been done (Bowker and Stoll 1988, Loomis 1989, Carson, et al. 1996) showing that CVM results provide legitimate welfare estimates that are comparable to RP results, criticism of CVM techniques have become more focused and direct overtime (Boyle 2003).

On the other hand, RP models also have some problems associated with sensitivity of welfare estimates to treatment of travel time and econometric issues. For years now, econometric efforts to develop RP models of recreation have evolved. Two main approaches have become the mainstream way to tackle non-market valuation using RP models. These are trip frequency travel cost (TCM) and random utility travel cost models (RUM-TCM). In both cases, econometric estimation has evolved from relatively simple computational methods that were not always consistent with the underlying data generating process, to more sophisticated methods that are more consistent with the nature of trip data.

Fully parameterized trip frequency count data models have gained ground with the use of Poisson, Negative Binomial and Multinomial Count Distributions in recreation literature (Creel and Loomis 1990, Hellerstein and Mendelsohn 1993) reflecting the integer nature of trips taken. The evolution of fully parametric trip frequency model have made RP models trustworthy (Hellerstein 1999).

In 1992 Cameron proposed a procedure that combined RP and SP methods in a simultaneous estimation framework. The purpose of this was to allow communication between models and to arrive at a robust estimation of both set of parameters. In Cameron's study, CVM estimation is combined with a TCM in a structural way, allowing CVM parameters to be conditional to expected demand levels for each individual. This first attempt used a probit and a normal distribution joint process. The simultaneous estimation done in Cameron's paper relates the errors in both methods assuming a bivariate normal distribution, conditioning the probit part of the estimation to the error structure in the TCM portion. The whole concept of joining these two estimation processes emanates from the idea that both CVM and TCM decision processes follow the same underlying principles and that combining both sets of information should help us reduce uncertainty regarding the resulting welfare measures.

However the SP part allows the researcher to explicitly evaluate policy relevant scenarios that may involve changes in resource quality beyond the levels observed in the RP data. This "data augmentations" approach avoids extrapolating beyond the range of the RP data when evaluating substantial improvements in environmental quality. Such non marginal changes in environmental quality are often associated with major restoration programs or updating decades old hydropower licenses or decades old land management plans.

For this research we follow the spirit of Cameron's (1992) work, by combining CVM and TCM data to estimate joint parameters. Unlike Cameron's approach, however our attempt is primarily computational and does not use a combined utility function to channel the TCM model information into the CVM choice parameters. Our approach provides us with a joint error structure but eliminates the need for parameter restrictions as no utility function needs to be determined (thus, parameters are not to be constrained across equations). Although this study still follows the basic approach of Cameron's combination of TCM and CVM data, it updates the joint estimation process by taking advantage of the evolution in parametric estimation models for TCM data. That is, we use a modified Poisson and Negative Binomial distribution to exploit the count nature of the TCM data. Furthermore, these distributions are modified to account for on-site sampling, a problem also known as endogenous stratification.

Also, the study focuses on the usefulness this joint estimation has on obtaining welfare measures. To assess whether welfare calculations differ between individual and joint estimations we use an empirical numeric procedure known as *complete combinatorial convolutions*. Poe, et al. (2005) proposed this method as an alternative to empirically determine the probability that a random variable is statistically different to another. We recognize that individual's willingness to pay (WTP) in both CVM and TCM models is a random variable and test whether calculated consumer surplus changes significantly from one case to another (joint and individual estimation).   Rather than conditioning the CVM data on the TCM, we adopt the spirit of Randall's (1998) suggestion that we learn everything that can be learned from combining these data without imposing preconceived notions regarding about the superiority of one type of data over another.

The following sections will expand on the econometric estimation process and the use of the convolutions method. Results and conclusions are also presented.

Alternative Ways to Combine TCM and CVM Data

Economists have pointed out that one can combine these two non market valuation methods in different ways. First and foremost, TCM's aim is to estimate a demand function while CVM looks at an inverse demand. Just as in Cameron's work, the unobservable factors that affect respondents' answers to the CVM question are likely to affect their number of trips demanded.

There is a continuum of TCM and CVM questions, ranging from seasonal WTP for both (Cameron 1992) to marginal trips for both (Loomis 1997). Loomis (1997) proposed to combine TCM and CVM in a series of dichotomous choices. In this view, the revealed trip making behavior reflects an implicit yes to the first of the bid questions at existing travel cost, whereas the CVM question represents the second response to a higher bid in a panel. The problem with using such approach is that you need to discard the trip frequency information from the TCM to be able to use it in a dichotomous choice panel context. Others, like Englin and Cameron (1996), do quite the opposite, setting up the CVM question in a way that mimics the TCM framework using a change in trips in response to higher travel costs. It has been argued that, in this case, asking visitors to reassess a full season of trips given a marginal change in price might be too much of a strain, thus becoming a source of possible bias or item non responses.

This objective of this paper is to simultaneously estimate both models to take advantage of the commonalities between the two methods and without: 1) discarding TCM trip frequency information, 2) forcing users to reassess their visits for the full season and 3) imposing consistency between the two models (e.g. instead, allowing testing for consistency). Our paper fills an important empirical gap in the analysis of combined RP and SP data: The case of TCM, with CVM on the most recent trip. This combination is not uncommon in the literature. Examples of separate use of these particular data setup can be found in studies that range from from deer hunting (Loomis, et al. 2000), mountain biking (Fix and Loomis 1998) to recreation demand in developing countries (Chase et al. 1998). The aforementioned commonalities imply that, as Cameron said, the underlying behavior in TCM and CVM should be related and that proper simultaneous estimation of both models should result in gains in efficiency.

It is important to update the Cameron (1992) approach to allow for count data models. Ever since Hellerstein and Mendelsohn (1993) established the theoretical foundation for the use of count data models, most recreation economists agree that count models can and should be employed because of their usefulness dealing with discrete and non-negative trips. In their definition of a discrete good demand function Hellerstein and Mendelsohn observe that the graphical shape of this demand schedule would look like a set of stairs. Each level of these stairs represented the extent to which a set of trips would be taken, given a certain price level.

Data

Data for this study come from a research project that is currently being conducted in the Caribbean National Forest in the northeastern part of Puerto Rico, also known as El

Yunque. Surveys were administered during the summers of 2004-05 as part of a comprehensive study on the impact of site characteristics on social and physical conditions in and around the forest streams.

In person interviews were conducted at nine recreation sites along the Mameyes and Espíritu Santo rivers. Data include visitor's demographics, site characteristics (fixed and variable), trip information and a contingent valuation question in the form of; "if the cost of this visit to this river was $____ more than what you have already spent, would you still have come today?" Bid amounts ranged from $1 to $200 per trip.

Over 700 observations were obtained and coded, of which 494 observations were used in this analysis. The reason for the reduction in observations is because only trips where visiting the site were the main reason for traveling are considered valid for the TCM. This is done to deal with multiple destination problems (274 trips were not single destination trips) that are typically pointed out as a source of distortion in travel cost models. Also, because of the complicated form of the corrected negative binomial distribution, we eliminated four visitors who took more than 100 trips because they appear to be from visitors that are somehow quite different than the vast majority who take a small fraction of these trips.

Variables in the TCM model include an **intercept** and **travel cost.** Variables in the CVM model include **mean annual stream discharge (as a measure of flow), distance of pool to bridge, pool volume, pool volume squared, median grain size (**measure of substrate sand size), and **gage day** (the depth of the river on the day sampled) and the bid amount visitors were asked to pay. Separate regressions indicate these variables have the greatest explanatory power under each model.

Likelihood Estimation

Estimating CVM parameters

Because CVM directly deals with consumer reactions to marginal changes they represent a straightforward way to obtain compensated welfare measures. In our study a dichotomous choice WTP question format is used. The welfare measure from a WTP question in CVM can be summarized in the following equation:

(1) $$v(p^0,Q^0,y) = v(p^1,Q^1,y-c)$$

where $v(\,)$ is an indirect utility function, p^0 is the current price level of the good considered, Q^0 is the current quantity of the good consumed and y is income. On the other side of the equation, p^1 and Q^1 represent the new price and consumption level and c is the Hicksian compensating variation or WTP. In words, this equation states that maximum WTP is the amount that makes utility levels equal when considering different prices levels, quantities and disposable income. Note that under the current condition (*0*), disposable income is y, whereas in the alternative scenario (*1*) is the difference between y and c.

What CVM allows us to do is to determine what the visitors' WTP is for the good in question. In other words, we uncover the population parameter c. In the case of recreation or site valuation the two levels available for consumption is typically all or nothing. Put differently, we uncover the WTP that makes the visitors indifferent between visiting a site or not on their most recent trip.

Because our WTP question format of "take it or leave it" involves a dichotomous choice of continuing to visit at the hypothetically higher travel cost or staying home, economists have used logit and probit likelihood functions to obtain WTP measures. For our purpose, this study uses a probit for the CVM portion of the parameter estimation. The general form of a probit likelihood function is derived from the Bernoulli distribution. A probit link is associated to ensure a non-negative and bounded probability value (between 0 and 1) while conditioning the individual probability function to the set of parameters to be estimated.

(2) $lnL = y_{cvm} * ln(\pi) + (1-y_{cvm}) * ln(1-\pi)$

where $\pi = \Phi(X\beta)$ and y_{cvm} is the individuals response to the CVM question. It is important to point that $\Phi(\,)$ stands for the standard normal cumulative density function; X refers to the set of variables we are conditioning our probability to and β is the set of parameters to be estimated. Among the set of variables X we have the bid amount or price increase per trip.

Estimating the TCM parameters

For the TCM portion of our estimation we use a Poisson and a Negative Binomial distribution. These two options are commonly used in the estimation of recreation demand because they are count data models. This means that they take advantage of two important characteristics (such as visits to a site) that count data share: non-negative and discrete outcomes. Both the Poisson and Negative Binomial have been used successfully in the past to estimate seasonal demand for sites.

One important consideration that was raised by Shaw (1989), and later showed empirically by Creel and Loomis (1990), is that truncated versions of these distributions should be used when on-site sampling takes place. Truncation of the dependent variable arises because all visitors must take at least one trip to be sampled. In addition, we also correct for what is known as endogenous stratification or the fact that on-site sampling results in an over-representation of more frequent visitors in the sample data.

In general correcting for truncation is done by dividing our probability distribution function by the probability of the ruled out (i.e., unobserved) outcomes. Analytically this could be represented as:

(3) $Pr(Y=y \mid y>\alpha) = Pr(Y=y) / Pr(Y>\alpha)$

In our particular case:

(4) $Pr(Y=y \mid y>0) = Pr(Y=y) / (1-Pr(Y=0))$

Note that because we are using count data models, we only need to find the probability that *Y* equals 0 and use its complement by subtracting it from 1.

When using the Poisson distribution, the resulting truncated version looks like:

(5) $Pr(Y=y \mid y>0) = (e^{-\lambda} \lambda^{y}) / (y!\ (1-e^{-\lambda}))$

where $\lambda = e^{(X\beta}$; and a resulting log likelihood function that can be represented in the following way:

(6) $lnL_{poisson} = -\lambda\ (y*ln(\lambda)) – ln(y!) – ln(1-e^{-\lambda})$

Alternatively, the Poisson distribution has a very particular and useful property for correcting for endogenous stratification. That is that the truncated Poisson distribution provides the same results as using a regular (without truncation) Poisson when subtracting 1 from the dependent variable *Y*.

However the Poisson imposes the restriction that the mean of the distribution equals its variance something often rejected by trip data. A more general form of the Poisson count data that tests for and relaxes this mean-variance equality is the Negative Binomial model. The standard log likelihood form of this model is:

(7) $lnL_{nb} = ln(\Gamma(y+(1/\alpha)))-ln(\Gamma\ (yTCM+1))-ln(\Gamma\ (1/\ \alpha))\ y*(ln(\alpha))+(y)*(ln(\lambda))-(y+(1/\ \alpha))*(ln(1+\ \alpha*\ \lambda)$

In the case of the Negative Binomial distribution this convenient property for correcting for on-site sampling does not hold. For this distribution an endogenously stratified version has to be derived resulting in the following log likelihood function:

(8) $lnL_{nb} = ln(y)+ln(\Gamma(y+(1/\alpha)))-ln(\Gamma\ (yTCM+1))-ln(\Gamma\ (1/\ \alpha))\ y*(ln(\alpha))+(y-1)*(ln(\lambda))-(y+(1/\ \alpha))*(ln(1+\ \alpha*\ \lambda))$

Simultaneous Estimation

Using Cameron's (1992) structure we define our joint estimation process taking advantage of the known fact that a joint probability is equal to a conditional probability multiplied by a marginal probability:

(9) $f\left(x,y\right)=f\left(x\mid y\right)f\left(x\right)$

Just as in her case, we define the conditional probability in a direct manner by making the CVM estimation conditional to the TCM expected outcome. This expectation is used as an avidity measure in the CVM part of the estimation. Although we use a non-linear distribution for our TCM estimation, the central limit theorem allow us to treat its errors as if they were normally distributed, thus making viable the use of the same conditional form for the probit part of the estimation. That is, assuming that we are dealing with a bivariate normal distribution where the expected value is ρZ and the variance is $(1-\rho^2)$. As should be understood, if the probit part of the estimation is treated as the conditional probability part of the aforementioned equality, the TCM (Poisson or Negative Binomial) part is considered as the marginal probability function. Analytically, our new CVM log likelihood function would then look like:

(10) $lnL = y_{cvm} * ln(\pi) + (1-y_{cvm}) * ln(1-\pi)$

where now $\pi = \Phi((X\beta+\rho Z) / (1-\rho^2)^{0.5})$ and $Z = (y_{tcm} - E(y_{tcm})) / \sigma_{tcm}$

The full log likelihood version of the joint estimation is simply the sum of the new CVM probit likelihood and the chosen TCM likelihood function (whether Poisson or Negative Binomial).

One point of clarification is necessary before finalizing this section. Special care must be taken when using the Negative Binomial modified distribution. Because we are correcting it for endogenous stratification, the first and second moments used in the definition of Z are not the ones usually considered, but are also modified to account for the correction. Englin and Shonkwiler (1995) define these corrected moments for the Negative Binomial as:

(11) $E(y |y>0) = \lambda +1+\alpha_0$

and

(12) $V(y | y>0) = \lambda +\alpha_0+\alpha_0\lambda+\alpha_0^2$

where $\alpha_0=\alpha/\lambda$.

To summarize, we will estimate recreation benefits with three empirical models: (1) the dichotomous choice CVM estimated with a probit model; (b) the TCM using Poisson and Negative Binomial; (c) a joint RP-SP model. From each of these models an estimator of net WTP for a trip is calculated. Now we turn to evaluation of whether these benefit estimates are different from each other and their respective CI's as a measure of the precision of the benefit estimates with each of the three methods.

Convolutions Method for Testing Differences in WTP

We use the method of convolutions to compare WTP estimates. Convolution is a mathematical operator that takes two functions and produces a third function that represents the amount of overlap between them. In 2005, Poe et al. proposed an alternative that can use a complete combinatorial approach to measure the difference between independent distributions. As mentioned before, convolutions create a third random variable that is formed by some relationship between the original functions considered. In Poe's example, this relationship is a difference between the two random variables of interest. This new random variable can be expressed as:

(13) $Z = X - Y$ *or*

(14) $Z = X + (-Y)$

Note that in (14) the difference is expressed by adding the *X* distribution to the distribution of *Y* flipped around zero (thus obtaining the negative value). Assuming that the corresponding probability functions of *X* and *Y* are $f_x(x)$ and $g_y(y)$ respectively, the distribution of their sum is represented by the following integral:

(15)
$$\begin{aligned} f \otimes (-g) &= h_z(z) \\ &= \int_{-\infty}^{\infty} f_x\left(z-(-y)\right) g_y(-y)\,dy \end{aligned}$$

This expression provides the probability that each combination of the original function produces. This can be shown to be related to the sum of the product of each combination from a polynomial multiplication. For a detailed proof please see Poe et al. (2005).

Although several approaches have been used to assess differences between benefit estimates, some important issues are addressed with the use of the complete combinatorial such as sampling errors from using random sampling or overstating significance from using Nonoverlapping Confidence Intervals. Finally, the convolutions approach does not require the assumption of normality for the resulting distribution. The complete combinatorial approach offers a simpler way to use the Empirical Convolutions Method. The empirical distribution of the difference can be expressed as:

$$(16) \quad \hat{X}_i - \hat{Y}_j = \hat{X}_i + \left(-\hat{Y}_j\right) \qquad \forall i = 1,2,3...,m \qquad j = 1,2,3...,n$$

where each difference is given the same weight.

The method assumes that the researcher generates two independent distributions that approximate random variables *X* and *Y*. As mentioned above, each event in both distributions is given the same probability, although repeated outcomes are easily incorporated without loosing generality. Poe et al. (1995) showed that this empirical application can be related to the summation of polynomial products which, itself, goes back to the formal definition of the convolutions method.

In our study, *X* and *Y* refer to WTP vectors for the individual and joint estimations respectively. A vector with random draws from the feasible values for each WTP is generated. A total of 4,000 draws were made and sorted. Each element of these vectors is subtracted from the other as suggested by (15). To obtain the one and two sided p-value the proportion of non-positive values is calculated. This represents the empirical probability that $\{x - y\} \leq 0$ or $\hat{\gamma}$ following Poe's notation. We use the convolutions method to test consistency between CVM and TCM joint and individual estimation.

Testing Efficiency Gains of Joint Estimation

As explained above the method known as convolutions allow us to assess the probability that two empirical distributions are different (whether WTP_{joint}=$WTP_{individual}$).

In our particular case we want to test whether the distribution of the WTP obtained from a joint estimation is statistically different from the one obtained in the individual estimation process. This allows us to test whether simultaneous estimation yields significantly different benefit estimates. There are other important ways in which we can see how different these results are from the ones obtained in separate regressions. For this matter we rely on more traditional hypothesis testing methods. That is, we use two different hypothesis tests to determine whether 1) the data generating processes of both equations are related in some way and, 2) if the resulting parameters for joint and individual estimations are equal. Formally this would be:

(17) $H_0: \rho = 1$ and $H_1: \rho \neq 1$

(18) $H_0: \beta^{joint} = \beta^{individual}$ and $H_1: \beta^{joint} \neq \beta^{individual}$

To determine whether to accept the null hypotheses in (17) and (18) we use the traditional t-test and likelihood ratio approach, respectively. We assess whether Rho is statistically different than one by using a t-test. To test equality of joint and individual coefficients we use the sum of log likelihoods of individual estimations against the joint estimation likelihood value. Together with the convolutions method, these set of tests should aid us to have a clearer idea of whether simultaneous estimation in this empirical case provides more efficient parameters.

Results

Results for the models estimated are summarized in table 1. The values shown are the parameters estimated value and their corresponding (t-values). This table shows results for the individual and joint estimations using the Negative Binomial (NB) distributions, as preliminary statistical results indicated that the overdispersion parameter *alpha* was statistically significant. This suggests that the Negative Binomial is closer to the actual data generating process and thus should be used rather than the Poisson when determining WTP.

As can be seen, theoretically consistent results were obtained for both TCM and CVM regressions. This results seem to suggest that our empirical case supports the theoretical expectation of negative slope parameters for travel cost and bid amount variables. The table not only reports the individual log likelihoods for the separate estimations, but also includes the sum of both TCM and CVM likelihood values. With regard to the hypothesis tests in (17) and (18), we can see that in the joint estimation Rho appears an insignificant variable.

Results for the likelihood ratio test performed between simultaneous and individual regressions are included in Table 1 also. The individual likelihood values for the separate regressions are reported along with the pooled log likelihood value. The difference between the sum of the individual log likelihoods and the simultaneous estimation likelihood is multiplied by 2 to obtain the likelihood ratio statistic χ^2 reported. The likelihood ratio value computed is not significant for the χ^2 test with one degree of freedom (critical value for 90% confidence level equals 2.706). With both an insignificant Rho value and likelihood ratio for the joint model, the joint estimation process, as used here, does not seem advantageous in our case study over the separate regressions approach.

Results from the tests done suggest that the CVM portion of the estimation is very robust because all parameters from individual and joint estimations are very close. The same applies to the TCM model.

In the case of the convolutions results, testing for significant differences in mean WTP, Table 2 provides a summary of the calculated confidence intervals for each model and two of the most commonly used confidence levels (90 and 95%). The values presented for maximum and minimum WTP in each case come from our convolutions method, thus these would vary in case of replication due to the random nature of the process.

Table 3 on the other hand, summarizes our failure to reject the null hypothesis of equality or no difference in separately estimated versus joint estimation of TCM and CVM benefits. Note that p-value under this test represents the probability that the difference between the two empirical distributions is less or equal to zero. These results seem to reflect the small gain in efficiency obtained with the joint estimation process in this case for our data. In our table, the comparisons between the joint and individual empirical WTP variables appear, for all practical purposes, identical for both the TCM and the CVM. The similarity of consumer surplus estimates from the individual and joint models can be seen in the near equivalence of the Travel Cost coefficients in Table 1. The individual Negative Binomial and Joint Negative Binomial model, the coefficients are again almost identical (-.0112 and -.0113) yielding consumer surplus per day of $88.

Since all comparisons between joint and individual estimations show us a one-tail p-value close to .5 (Table 3) we can understand that the entirety of one of the distribution tails is covered by the tail of the other distribution, thus one empirical distribution lies on top of the other. It is worth mentioning that the one-tail p-value for the empirical convolution between the TCM and CVM WTP (for the joint Negative Binomial estimation) was equal to .16. This suggests consistency between the two methods used to assess consumer demand.

Conclusions and future research

This paper provides an empirical modeling procedure that allows for testing whether joint estimation of stated and revealed preference models increase efficiency when compared to individual estimations and consistency between TCM and CVM responses. In our data the CVM WTP question involved willingness to pay to visit the site under current conditions, a scenario quite conceptually similar to what is estimated with TCM. In this situation the improvement from joint estimation was quite small. However, joint estimation may result in larger and significant efficiency gains in the situation where the CVM WTP scenario deviates substantially from the existing situation in terms of quality of the site. Empirically testing this conjecture awaits suitably designed CVM and TCM datasets.

Another avenue of future research would be to integrate both models more, perhaps updating the joint utility theoretical approach that Cameron (1992) used to reflect the utility structure of count data models presented by Hellerstein and Mendelsohn (1993). Another alternative is to derive the expected constraints for different utility specifications and again use the simultaneous equation or estimation only to test which utility specification is supported by the data.

For this case our simultaneous estimation process can be seen as a general unconstrained version of Cameron's earlier work and opens the door to determine which type of joint preferences should be used prior to the actual estimation. Due to the complexity of estimating a constraint utility theoretic specification, more information on the constraints that are supported by our empirical analysis should save researchers a great amount of effort while providing a better understanding of the behavior that guides both stated and revealed preferences.

At the methodological level, a contribution of this paper is updating the TCM portion of the joint estimation statistical technique used by Cameron to reflect the count data models now commonly used for recreational demand modeling. Using count data models represents an improvement over the original simultaneous estimation suggested by Cameron.

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Table 1. Results from individual and joint estimations

	Variable	Individual NB	Joint NB & Probit
TCM	**Intercept**	1.6465	1.646304
		15.4736	15.482901
	TC	-0.0113	-0.011259
		-5.6238	-5.635707
		Individual Probit	
CVM	**Intercept**	2.429484	2.415245
		4.363278	4.207129
	Bid	-0.010373	-0.010351
		-9.185037	-9.119293
	Road	-0.234723	-0.233110
		-2.466048	-2.376022
	Mean Annual Discharge	-1.113220	-1.109557
		-2.627327	-2.54502
	Median Grain Size	-0.000442	-0.000440
		-2.530866	-2.471221
	Pool Volume	0.002197	0.002187
		2.258765	2.227659
	Pool Volume2	-0.000001	-0.000001
		-1.976418	-1.961058
	Alpha	3.3296	3.329833
		3.425	3.425877
	RHO		-0.010433
			-0.276134
	Log Likelihood TCM	**-812.20970**	
	Log Likelihood CVM	**-261.30236**	
	Combined Log Likelihood	**-1073.51206**	**-1073.47540**
	Likelihood Ratio	0.07331	

Results present coefficients and t-values.

Table 2. Sumary for Convolutions WTP confidence intervals for individual and joint models.

		Joint				Individual			
		CI	MIN.	MEAN*	MAX.	CI	MIN.	MEAN*	MAX.
TCM	NB	**95**	$65.58	$88.82	$134.27	**95**	$65.46	$88.73	$136.70
		90	$69.12	$88.82	$124.78	**90**	$68.44	$88.73	$123.52
CVM	Probit	**95**	$95.37	$108.00	$160.62	**95**	$96.30	$109.31	$126.78
		90	$97.33	$108.00	$156.13	**90**	$98.23	$109.31	$123.57

*Means are calculated using $1/\beta_{tc}$ for the TCM and $\beta_0 / abs\left(\beta_{bid}\right)$ where β_0 is a grand constant term (it includes all non bid coefficients multiplied by the respective mean value of the variables). Minimum and maximum values come from the convolutions method.

Table 3. Summary for Convolutions on Mean WTP for individual and joint Models (P-values for null hypothesis of equality of WTP between models).

		Joint	
		TCM	CVM
Individual	TCM	0.5	
	CVM		0.49